Forecasting Building Energy Consumption in Seoul using ARIMA under Climate Change and Socioeconomic Scenarios

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ABSTRACT

For the Seoul Metropolitan Government to meet the goal of 2050 carbon neutrality, there is a crucial need to understand future building energy consumption for more informed policy-making. Seoul consists of 25 districts, which make up six communities. This study aims to predict residential electricity uses in six communities of Seoul Metropolitan City under different future development scenarios. A total of 25 prediction models corresponding to 25 districts in Seoul were constructed using seasonal ARIMA with exogenous variables. The models consider cooling degree days (CDD), heating degree days (HDD), total population, older adult ratio, and GRDP from 2010 to 2019 as predictive variables. Electricity consumption from residential buildings in each district at the end of the year 2050 was then estimated from the models under four development scenarios. The four scenarios were defined based on two SSP-RCP climate change scenarios and two Korean Statistical Information Service (KOSIS) socioeconomic scenarios. The forecasting results were aggregated at the community level in Seoul. The aggregated results indicated that even under the same sets of scenario assumptions, the trend of future residential energy change varies across different communities. Therefore, different measures should be taken when implementing community-level plans to reduce building energy.

Keywords: building energy forecasting, urban development scenarios, community development plan, carbon neutral city development,

NOMENCLATURE

Abbreviation	S
	Autoregressive Integrated Moving
ANIIVIA	Average
SMG	Seoul Metropolitan Government
SSP	Shared Socioeconomic Pathways
RCP	Representative Concentration pathways

1. INTRODUCTION

The International Panel on Climate Change (IPCC) projected that the goal to limit the global temperature rise of this century well below 2°C compared to the preindustrial level is only possible when global carbon neutrality is achieved by the year 2050 [1]. Along with the global consensus to take more proactive measures to achieve net-zero by 2050, Seoul Metropolitan Government (SMG) pledged for 2050 carbon neutrality and submitted climate action plan to the C40 [2]. As the building energy consumption sector accounts for 68% of the total GHG emitted from Seoul, meeting this goal heavily relies on reducing building energy consumption by designing an energy-efficient urban environment [3].

The identification of climatic, socioeconomic, and urban form factors that can potentially influence building energy consumption has been thoroughly investigated in the literature [4-8]. Based on the results from descriptive studies, research on predicting building energy use has been conducted. The field where the topic is most frequently investigated is architecture engineering, the main focus point being on building optimization [9-13]. With the rising importance of carbon neutrality, a number of scholars have recently started exploring the future changes in building energy consumption on larger scales [14-18]. However, prediction study which adopted scenario frameworks to identify the uncertainties of future conditions was hard to come by. Furthermore, previous studies only examined future changes in national or metropolitan city-scale energy consumption, with compromised prediction accuracy and limited suggestions for urban planners and policymakers.

The purpose of this study is to investigate the influence of climate change on electricity consumption from residential buildings in six communities in Seoul. Seoul consists of 25 "Jachi-gu" (hereby districts), wich is the unit that SMG collects data most frequently. Under

the current masterplan of Seoul, the smallest scale of the legally regulated urban plan is "The Community Plans". By this, the SMG categorizes the 25 districts into five communities depending on the characteristics of each district and implements different urban designs accordingly. As one of the communities is divided into two, the total number of communities in Seoul makes up six.

2. METHODOLOGY

2.1 Research Range



Fig 1. Map of Seoul Metropolitan City 25 districts and six communities

The study area is Seoul Metropolitan City in South Korea. The subject of study is electricity consumption from residential buildings. The spatial unit of the prediction model is the district, and the analytical unit is the community. The temporal scope is from 2010 to 2050, and the temporal unit is a month.

2.2 Variables and Data

Table 1 shows the data list of this study. A panel dataset consisting of one output variable and five input variables in the 25 districts was constructed. Historical and future data were collected from different sources.

2.2.1 Historical Data

Electricity consumption data was collected from the SMG data plaza. Cooling degree days (CDD, base=24°C) and heating degree days (HDD, base=18°C) were calculated using 1km² resolution of daily average, minimum, and maximum temperature data provided by the meteorological administration. Socioeconomic data were achieved from Korean Statistical Information Service (KOSIS). Table 2 shows the descriptive statistics of the pooled data.

Table 2. Historical data descriptive statistics (pooled)

	Residential electricity	Gross Regional Domestic	Population	Older Adult	CDD	HDD
count	3000	250	3000	3000	3000	3000
mean	44106.88	14787890	402270	12.45	23.72403	226.0964
std	14935.74	14478381	129552	2.38	38.40983	232.1346
min	13438	2759140	123926	7.3	0	0
25%	34469.5	5681345	326712	10.7	0	5.761816
50%	43474	7912257	402221	12.4	1.383267	130.5353
75%	52502.25	18496525	489712	14.2	34.17518	432.2714
max	118932	67789806	686982	19.3	179.9812	827.4426

2.2.2 Future Data

In examining the energy consumption under different levels of climate change conditions, this study utilized SSP (Shared Socioeconomic Pathway) - RCP (Representative Concentration Pathway) Scenario

Division	Category	Variable Name	Contents	Historical data t (t unit)	Historical data N	Future data t (t unit)	Predicted Future data N	Data Source
Output Variable	Building Energy Residential electricity consumption Consumption		electricity consumption in residential buildings		3,000			Seoul Metropolitan Government
Input Variable	Climate	CDD	Average cooling degree day of 1km*1km grid in each district	2010.01 ~ 2019.12 (monthly)	(12 month *10 years *25 districts)	2020.1 ~ 2050.12 (monthly)	9,300 (12 months *31 years *25 districts)	Korean Meteorological Administration
		HDD	Average heating degree day of 1km*1km grid in each district					
	Socio Economic Factors	GRDP	Gross Regional Domestic Products (2015 base)	2010 ~ 2019 (yearly)	250 (10 years *25 districts)		775 (31 years *25 districts)	Korean Statistical Information Service
		Population	Total registered population	2010.01 ~	2010.01 ~ 3,000 2019.12 (12 month 2019.12 *10 years monthly) *25 districts)	2020 ~ 2050 (yearly)		
		Older Adult Ratio	Percentage of Older Adult among total population	(monthly)				

Table 1. Variable List

* yearly frequency data were adjusted to monthly frequency using linear interpolation method in the analysis

Framework to collect future climate data. Provided by the IPCC, the framework contains 20 sets of climate projections, and in this study, only SSP1-RCP2.6 (SSP126) and SSP5-RCP8.5 (SSP585) were used. SSP126 represents the climate condition resulting from a sustainable society with very low GHG emissions, whereas SSP585 demonstrates the climate resulting from fossil-fueled development and very high GHG emissions. In order to address the inherently unpredictable nature of the future, the "Low" and "High" demographic scenarios from KOSIS were used. The name of the scenarios represents their assumptions on birth rate, life expectancy, and net migration. The future values of GRDP were retrieved from the Financial outlook report written by the Seoul Institute [19]. A total of 4 combinations of future scenarios (Low-ssp126, Highssp126, Low-ssp585, High-ssp585) were made and used as future inputs to forecast the residential energy consumption of each district. Table 3 shows the descriptive statistics of the pooled data.

Table 3. Future data descriptive statistics (pool

Scenarios	Baseline	Low		High		SSP126		SSP585	
		Older		Older					
Variables	GRDP	Adult	Population	Adult	population	CDD	HDD	CDD	HDD
count	775	775	775	775	775	9300	9300	9300	9300
mean	22827619.08	28.76	336007.8	27.66	364733.8	34.44748	196.9043	37.71069	188.7972
std	22925718.7	7.8	111599	7.00	117443.4	54.28337	211.0331	58.42357	203.4314
min	3001395.817	13.07	92282.28	13.07	111285.2	0	0	0	0
25%	7775463.551	22.44	271241.2	22.14	299119.1	0	2.939122	0	2.190625
50%	12578712.78	28.94	334613.9	27.92	364344.6	1.790104	103.9282	1.943961	102.2319
75%	29157432.97	34.72	409877.3	32.94	440695.5	51.92248	382.4733	59.81849	356.7683
max	117784118.1	47.24	641653.8	43.95	641653.8	242.0937	763.0222	264.7804	717.4667

2.3 Method

2.3.1 Prediction Models

Using the historical monthly data from 2010 to 2019, 25 Seasonal Autoregressive Integrated Moving Average with exogenous variables (SARIMAX) models were constructed independently. As a time-series univariate regression model, SARIMAX models can predict future values of independent variables while accounting for serial autocorrelation and seasonality in the data. There are six parameters to be set for constructing a SARIMAX model (p,d,q, and P,D,Q). Auto_arima module in Python pmdarima library [20] automatically sets the best possible parameters of a SARIMAX model with an optimization procedure. The residuals of generated 25 models using auto arima were diagnosed with Augmented Dickey-Fuller test and Ljung-Box test, and those that contained unit root and autocorrelations in the residuals were adjusted manually.

2.3.2 Climate Change Scenarios

Two climate change scenarios were adopted in this study. Fig 2 shows the average annual surface air temperature of the five communities under the two climate change scenarios. Under SSP126, the monthly temperature in summer will rise 2.28°C in July, 2.76°C in August, 2.06°C in September while under SSP585 it will be 3.39°C, 3.37°C, and 2.93°C respectively. In winter, monthly temperature will rise by 0.79°C on December, 1.08°C on January, and 0.82°C on February under SSP126, and 2.39°C, 2.4°C, 2.14°C under SSP585.



Fig 2. Change of Annual average temperature

2.3.3 Scio-economic Scenarios

By 2025, the average percentage of older adults of Seoul under both Low and High scenarios passed 20%, entering a "Super Aged Society" by definition. At the end of the year 2050, the average older adult ratio of Seoul went up to 39.25% under the Low scenario and 36.51% under the High scenario. The level of aging was most severe in Community 1 (CBD area), with 44% being the older adult population. The total population in Seoul was a 9.6million at the end of 2019. However, it will decrease to 7.2 million under the Low scenario and 8.6million under the High scenario.



fig 3. Residential electricity consumption forecasting of Gangnam-gu, under 4 scenario combinations

3. RESULTS AND DISCUSSION

3.1 Model Results

All 25 models passed residual diagnostics. The average prediction error rate of all models was calculated by NRMSE (Normalized Root Mean Squared Error) and MAPE (Mean Absolute Percentage Error). The NRMSE mean is 0.102 and MAPE mean is 12.78. The error rates of building energy consumption models varied from 1% to 50% in the reviewed literature [14-18]. Therefore, it can be concluded that the model performance was in an acceptable range.

Та	ble	24.	Мос	lel	prediction	performance	results
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Model	Evaluation: NRMSE	Evaluation: MAPE
District1	0.0796	14.061
District2	0.0833	12.148
District3	0.0691	12.655
District4	0.0779	12.020
District5	0.0646	13.110
District6	0.0782	11.637
District7	0.1372	12.913
District8	0.0669	13.863
District9	0.0755	11.322
District10	0.088	13.368
District11	0.112	13.172
District12	0.077	14.078
District13	0.100	12.915
District14	0.217	9.7478
District15	0.114	13.400
District16	0.073	12.288
District17	0.060	12.036
District18	0.200	10.402
District19	0.088	15.679
District20	0.068	13.896
District21	0.123	13.411
District22	0.153	14.420
District23	0.124	14.135
District24	0.064	12.893
District25	0.171	10.142
mean	0.102	12.788

3.2 Forecasting Results

Every district's residential electricity consumption was forecasted under four combinations of climatic and socioeconomic scenarios, as shown in figure 3. A total of 100 predictions were conducted. Then the forecasting results were aggregated at the community level. Figure 4 and Table 5 show the residential electricity consumption in the 2010s (historical data, 2010 ~ 2019), 2020s (2020 ~ 2029), 2030s (2030 ~ 2039), and 2040s (2040~2049).

Community 1 is a Central Business District of Seoul. Residential electricity consumption in Community 1 is expected to rise by 74.56% (High- ssp126) to 81.47% (Low-SSP126) by the start of 2050. Community 2 is the commercial area and is the only community whose predicted residential electricity consumption is expected to decrease by the range of 13.28%(High-SSP585) to 27.23% (Low-SSP126). Community 3 is one of the residential areas but is closer to downtown. Residential electricity consumption is also predicted to rise by 26.92% (Low-SSP126) to 33.08% (High-SSP585). Community 4 is also a residential area. However, no significant change in residential building energy consumption is expected. Community 5 is considered to be an industrial area, and the increasing percentage of residential electricity consumption is from 23.35% (Low-SSP126) to 29.95% (High-SSP585). Lastly, Community 6 is a cultural and artistic area with a number of tourist destinations. Residential electricity use is expected to rise by 24.99% (Low-SSP126) to 31.46% (High-SSP585) by the start of 2050.



Fig 4. Forecasting results

Table 5. Forecasting Results

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		Seoul	C1	C2	C3	C4	C5	C6
Decade Sum of Electricity Use in Residential Buildings								
Residentia	l electricity	/ consump	tion (Kw	h): 2010	Os			
Histo	orical	132,321	8,304	29,790	18,512	21,298	38,934	15,483
Residentia	l electricity	/ consump	tion (Kw	h): 2020	Os			
SCD126	Low	135,930	10,215	27,116	19,846	20,278	41,885	16,590
33F120	High	137,028	10,203	27,514	19,961	20,498	42,162	16,690
CCDEQE	Low	136,260	10,239	27,193	19,890	20,330	41,978	16,630
337363	High	137,359	10,227	27,591	20,005	20,550	42,255	16,731
Residential electricity consumption (Kwh): 2030s								
SSP126	Low	141,532	12,891	23,869	21,720	19,814	45,203	18,036
	High	146,779	12,771	25,850	22,264	20,907	46,481	18,506
CCDEQE	Low	141,951	12,924	23,981	21,781	19,875	45,306	18,084
335303	High	147,198	12,804	25,962	22,325	20,967	46,584	18,555
Residentia	l electricity	/ consump	tion (Kw	h): 2040	Ds			
SSD126	Low	147,235	14,917	21,676	23,496	19,764	48,029	19,353
SSP126	High	156,228	14,495	25,353	24,415	21,775	50,067	20,122
CODERE	Low	149,185	15,069	22,154	23,759	20,056	48,561	19,586
SSP585	High	158,177	14,648	25,831	24,677	22,068	50,598	20,355

4. CONCLUSION

This study forecasts future residential electricity consumption in Seoul under different sets of scenarios on climate change and socioeconomic shifts. Three communities (Community 3, 5, 6) were expected to experience an increase in residential energy consumption, and the changing range was the biggest under the High-SSP585 scenario. However, another community (Community 1) was predicted to have the same trend, but the expected gap between current energy use and the 2040s' was the biggest under the Low-SSP126 scenario. Moreover, energy use in Community 2 was predicted to decrease significantly under all four sets of future scenarios. This indicates that even under the same set of assumptions on the future, future consumption of energy can vary within the metropolitan city. Therefore, such spatial variations must be taken into account when implementing for designing energy-efficient measures urban environments.

Theoretically, this study did not consider the emergence of disruptive technologies. Instead, it examined how future energy use will change under the assumption that current climate and socioeconomic trends persisted so as to provide implications to urban planners and policymakers to deal with the predictable range of the future. Methodologically, the study ignored the spatially correlated nature of energy use and constructed independent prediction models for all the districts separately. Machine learning models such as Long-short term memory models will be applied in future works to use the panel data fully.

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REFERENCE

[1] IPCC. Global warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change. 2018. [2] SMG. 2050 Seoul Metropolitan City Climate Action Plans; 2021.

[3] SMG. 2019 Seoul Greenhouse Gas Inventory Report. 2021.
[4] Moral-Carcedo J, Perez-Garcia J. Temperature effects on firms' electricity demand: An analysis of sectorial differences in Spain. Applied Energy. 2015;142:407-25.

[5] Li J, Yang L, Long H. Climatic impacts on energy consumption: Intensive and extensive margins. Energy Economics. 2018;71:332-43.

[6] Brounen D, Kok N, Quigley JM. Residential energy use and conservation: Economics and demographics. Eur Econ Rev. 2012;56:931-45.

[7] Shahbaz M, Sarwar S, Chen W, Malik MN. Dynamics of electricity consumption, oil price and economic growth: Global perspective. Energ Policy. 2017;108:256-70.

[8] Chen YJ, Matsuoka RH, Liang TM. Urban form, building characteristics, and residential electricity consumption: A case study in Tainan City. Environ Plan B-Urban. 2018;45:933-52.

[9] Ye Young Lee, Geun Young Yun. The expectation of future heat island effect and influence of climate change in building energy consumption in Seoul. SAREK Summer Congress. 2015;15-5-055:pp 208~11.

[10] Somu N, Raman M R G, Ramamritham K. A deep learning framework for building energy consumption forecast. Renewable and Sustainable Energy Reviews. 2021;137.

[11] DS Gong, Younghoon Kwak, Huh Jung-Ho. Artificial Neural Network based Energy Demand Prediction for the Urban District Energy Planning. 2010;26:221-30.

[12] Gassar AAA, Cha SH. Energy prediction techniques for large-scale buildings towards a sustainable built environment: A review. Energ Buildings. 2020;224.

[13] D'Agostino D, Parker D, Epifani I, Crawley D, Lawrie L. How will future climate impact the design and performance of nearly zero energy buildings (NZEBs)? Energy. 2022;240.

[14] Liu S, Zeng A, Lau K, Ren C, Chan PW, Ng E. Predicting long-term monthly electricity demand under future climatic and socioeconomic changes using data-driven methods: A case study of Hong Kong. Sustainable Cities and Society. 2021;70.

[15] Zheng SG, Huang GH, Zhou X, Zhu XH. Climate-change impacts on electricity demands at a metropolitan scale: A case study of Guangzhou, China. Applied Energy. 2020;261.

[16] Gunay ME. Forecasting annual gross electricity demand by artificial neural networks using predicted values of socioeconomic indicators and climatic conditions: Case of Turkey. Energ Policy. 2016;90:92-101.

[17] Chabouni N, Belarbi Y, Benhassine W. Electricity load dynamics, temperature and seasonality Nexus in Algeria. Energy. 2020;200.

[18] Zuo ZL, Guo HX, Cheng JH. An LSTM-STRIPAT model analysis of China's 2030 CO2 emissions peak. Carbon Manag. 2020;11:577-92.

[19] Seoul Institute. Seoul Metropolitan Government long term financial outlook report. 2018.

[20] Smith, Taylor G., et al. pmdarima: ARIMA estimators for Python, 2017-, http://www.alkaline-ml.com/pmdarima [Online; accessed 2022-08-13].